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A Study on the Application of Google Earth Engine for Precipitation Monitoring

Weicheng Lin*

School of Atmospheric Sciences, Nanjing University of Information Science and Technology, Nanjing, China

**Corresponding author: Weicheng Lin.*

Abstract

Monitoring precipitation is an important basis for climate change studies and for the prevention and control of hydrological disasters. There are currently skewed distributions of ground-based meteorological observation stations, and satellite-based precipitation products still lack sufficient spatial resolution and systematic accuracy, directly influencing the accuracy of runoff models and early flood and drought warning systems. In this paper, the advancement in precipitation monitoring on the Google Earth Engine (GEE) platform was reviewed. It methodically evaluates the synthesis and use of mainstream precipitation products, including IMERG, CHIRPS, and ERA5-Land, as well as complementary information on topography and vegetation, and ground-truth validation data on the GEE cloud platform. The article focuses on the essence of technical workflow procedures for the precise spatial resolution of precipitation in complex terrain and urban environments by combining spatial-decay techniques with machine-learning algorithms, including Random Forest and XGBoost, on the platform. It also examines existing issues, such as inefficiencies in the parameter optimisation of prebuilt algorithms at GEE, the lack of deep learning functionality, and the inability to validate multi-source precipitation products under extreme precipitation conditions. Moreover, the paper outlines future development directions, including deep integration with external AI frameworks and the implementation of higher-resolution spatiotemporal observational data.

Keywords

satellite remote sensing, precipitation monitoring, Google Earth Engine

1. Introduction

Precipitation plays an essential role in the global water cycle, and its spatiotemporal variations significantly affect the distribution of water resources in the region, ecological processes, and the survival of natural disasters, including floods and droughts. In the context of climate change, the spatiotemporal distribution of precipitation is characterised by high uncertainty and regional variability, and the proportion of extreme precipitation events increases in certain regions. Thus, it is particularly important to conduct long-term, continuous, and high-precision precipitation monitoring studies to understand climate change processes better and enhance disaster prevention and mitigation [1].

In the modern world, the main sources of precipitation monitoring are ground-based weather station measurements and satellite-based remote sensing data. This is because ground-based meteorological stations are useful for providing credible precipitation data, but have very limited spatial coverage. The use of satellite-based precipitation products has steadily become a valuable source of data with the evolution of remote sensing technology; such missions include TRMM (Tropical Rainfall Measuring Mission) and GPM (Global Precipitation Measurement mission), which have provided continuous global precipitation measurements [2]. Moreover, there are multi-source fusion products, including the CHIRPS precipitation dataset and the ERA5 reanalysis dataset, which are actually used in climate change and hydrological studies [3]. Nevertheless, such precipitation products have limited spatiotemporal resolution and systematic biases (e.g., high-intensity rainfall is overstated and solid-state and trace precipitation are underestimated). This can lead to an inversion in the spatial distribution of precipitation within a watershed, thereby undermining the reliability of runoff simulation, early flood and drought warnings, and water resource distribution. GEE, with its built-in big-data and cloud-computing solutions, can be used to merge, evaluate the quality of, and analyse multi-source precipitation data, which could help overcome barriers such as high data acquisition costs, data-heavy preprocessing, and limited computing power and throughput [4]. Thus, it is of great importance to synthesise the research achievements in the domain of GEE for precipitation monitoring. The current paper reviews recent precipitation-monitoring research conducted on the GEE platform and serves as a reference for related work.

It is against this development backdrop that this paper will take a logical structure of Platform and Data Sources, Key Methods, Applications and Outlook. First, it presents an overview of the background and methodological value of the GEE platform, second, it presents the precipitation products and validation data systems that are accessible using GEE, third, it summaries typical workflows that include remote sensing inversion, spatial downscaling, and machine learning, and lastly, it explains current challenges and the future research directions to become an academic source of high resolution precipitation monitoring studies using GEE.

2. Methodological Value of Gee in Precipitation Monitoring Research

2.1 Platform Background and Technical Framework

GEE is a distributed geospatial big-data analytics platform, a cloud-based system created and managed by Google to support research on environmental change at a global scale. It is a platform that integrates multi-source remote sensing, reanalysis, and meteorological observation data and provides online computing services based on a distributed parallel computing framework.

In hydrological studies, the usefulness of GEE goes beyond the ease of data access; it is characterised by providing a common computational platform for examining and processing precipitation data across long time series at a variety of spatial scales. This homogeneity is crucial for watershed-scale hydrological modelling and climate change response studies.

2.2 Precipitation Monitoring Data Sources of Gee

The essence of precipitation monitoring lies in selecting and processing data sources. Since GEE is a cloud-based centre intended to enable global-scale geospatial analysis, its key benefit is the combination of multi-source Earth observation data and a range of environmental information spanning more than 40 years, which offers a one-stop database for the study of precipitation values on a large-scale, long-term basis. The platform not only efficiently combines long-term image series from mainstream imagers such as Landsat, MODIS, and Sentinel, but also methodically presents multidimensional data on topography, meteorology, land cover, and socioeconomic variables. This allows scientists to go beyond the constraints of individual data sources and easily retrieve and jointly process multiscale, multiplex data on precipitation processes through an integrated cloud platform [5]. According to this, the precipitation monitoring data ecosystem created by this paper via GEE comprises three main tiers: core satellite precipitation products, key environmental covariates, and ground-based validation data. The remainder of this paper provides a systematic overview and explanation of the data sources for each tier.

The use of satellite-based precipitation products as the central data source in precipitation monitoring research also requires that the most frequently used products have their own focus and unique research interests. With the GPM IMERG series, a third-generation advancement of the TRMM mission, the latest state-of-the-art multi-satellite combined precipitation retrieval exists. It combines passive microwave, infrared remote sensing, and ground-based rain-gauge data through calibration, fusion, and interpolation algorithms to generate a world-gridded precipitation dataset [6]. In general, studies on the GEE platform apply the Final Run version (V06 or V07) calibrated by GPCC, which has high data reliability, the CHIRPS dataset is specifically designed to support drought monitoring and long-term climate change analysis and is based on high-resolution 0.05 o infrared data which combines observations made by world weather stations to deliver continuous global products of precipitation since 1981 [7]. Its longer length of the time series, and lower spatial resolution than IMERG, has led to its acceptance as a fundamental contributor to the long-term series of precipitation trends and interdecadal drought research: the land component of the ERA5 product, ERA5-Land, is based on superior data assimilation systems and numerical models, in achieving physically coherent inversion of land-surface variables like precipitation. It can exhibit spatiotemporal continuity and physical consistency due to its 0.1° spatial resolution and 1-hour temporal resolution, which is why it is widely used as a reference dataset to assess the plausibility of satellite precipitation products and to compare multi-source data.

Important environmental covariates can provide crucial assistance in downscaling precipitation patterns or even aid in the mechanistic analysis of the phenomenon. However, topography is the most important covariate when defining the spatial variation in precipitation conditions. To properly derive topographic parameters, i.e., elevation, slope, and aspect, the 30-meter-resolution SRTM Digital Elevation Model (DEM) data made available by the GEE platform can be used to correct systematic biases in satellite-based precipitation products, such as IMERG, in complex terrain, such as mountainous regions [8]. The vegetation and surface thermal state data (MODIS NDVI/EVI and LST) are also considered crucial: the vegetation indices are relevant indicators of surface moisture conditions and the potential for evapotranspiration, whereas the surface temperature is directly proportional to the severity of local convective activity. Both are lagging or instantaneous measures of precipitation and are fundamental input characteristics for high-resolution precipitation forecasting. In addition, ancillary information, e.g., land cover types and proximity to water bodies, also contributes to a more in-depth characterisation of the complex effects of surface characteristics on the spatial distribution of precipitation. A combination of all these covariates allows the coarse-resolution precipitation fields to be downsampled to the kilometre or even hundred-meter scale, thereby realising greater utility for fine-tuning hydrological management and disaster anticipation and control.

Ground-based validation data provide direct support for the analysis and calibration of the accuracy of satellite precipitation products. GEE has an embedded Global Summary of the Day (GSOD) database that includes basic meteorological parameters, such as daily precipitation. Direct code can be written to retrieve station data for specific locations and centuries to compute accuracy metrics, including correlation coefficients, root-mean-square error, and bias, and to contrast them with satellite precipitation products. This is one of the most widely used data sources for confirming precipitation products. In areas where ground observation networks are well established (as is the case in China), on top of the above global data, there is frequently a combination of high-density station data issued by organizations like the National Meteorological Information Centre (it can be accessed by uploading user-ownable content in GEE or connecting to other APIs) to more stringent and granular local accuracy measurements [9].

3. Monitoring Precipitation Using Gee

3.1 Remote Sensing Inversion Method

One of the most popular approaches to the monitoring of precipitation is remote sensing inversion. In the quest to improve inversion accuracy, research usually integrates downscaling approaches with machine learning algorithms. Satellites such as TRMM and GPM provide precipitation products characterised by temporal continuity and extensive spatial coverage, thereby supporting global and regional precipitation estimates and playing important roles in monitoring both short-duration heavy precipitation and extreme weather [2, 10]. To enhance the reliability of local precipitation forecasts, scientists typically combine satellite data and ground-based rain gauges. They construct precipitation prediction models using machine learning or statistical methods, incorporating environmental factors such as elevation, vegetation indices, and land cover to improve inversion performance in complex terrain and urban areas [11, 12]. With the GEE platform, researchers will have direct access to various satellite-based precipitation products and the ability to fuse them with other auxiliary data, including MODIS vegetation indices and SRTM elevation data, for spatial and temporal matching and preprocessing. This facilitates spatial downscaling and high-resolution retrieval, as well as the joint operation of various methods.

3.2 Spatial Downscaling Method

There are also significant benefits to the spatial downscaling of precipitation products provided by GEE. Using the example of TRMM 3B43 V7, the instrument's 0.25° spatial resolution is not very favourable for imaging the spatial heterogeneity of precipitation in small-watershed or urban-scale studies due to topographic and land-cover differences. TRMM precipitation data, vegetation indices (NDVI, EVI, and LAI) from MODIS, SRTM elevation, and latitude/longitude can be accessed online using the GEE platform. Multi-source data are unified via spatiotemporal registration in the cloud, followed by the construction of predictor datasets at two resolutions: 25 km and 1 km. On this basis, nonlinear models of precipitation influenced by geographic environmental factors are developed, with coarse-resolution precipitation data downsampled to 1 km. The residual correction and scale decomposition methods are then used to generate finer-resolution spatiotemporal precipitation products, and ground station information is utilised to assess accuracy and conduct spatial pattern analysis. The complete workflow leverages GEE's strength in processing massive volumes of remote sensing data, cloud computing, and multi-scale raster operations to bring TRMM precipitation down to 1 km resolution [13].

3.3 Machine Learning and Artificial Intelligence Methods

Machine learning and artificial intelligence technologies are now available through the GEE platform, offering new directions in precipitation monitoring, with considerable benefits for complex terrain, multi-source data fusion, and high-resolution inversion. Using combinations of satellite precipitation products, ground-based observation data, and auxiliary variables (elevation, vegetation indices, and land cover), regression and classification models can be developed in the cloud to provide nonlinear estimates of precipitation. Random Forest, XGBoost, and CNN models are also efficient at capturing spatial features of precipitation, and the LSTM model is better placed to capture temporal changes [11, 12]. These are trainable, valid and predictable with an in-built EE in the GEE. Python or Classifier API, and take advantage of the benefits of cloud computing to process very large, all-around data in time-series [14]. It has been established that precipitation estimation is more accurate through machine learning than conventional models or single-satellite products. It is very effective in augmenting the detail and reliability of spatial distribution in mountainous locations, small watersheds and urban regions. Moreover, in conjunction with downscaling and residual-correction techniques, it may produce high-resolution, temporally continuous precious information that can reliably support disaster prevention and mitigation, water resource management, and climate-change studies [11, 12, 15].

4. Conclusion

This paper presents a systematic review of advances in precipitation monitoring using the Google Earth Engine cloud platform. The review states that by leveraging its strong cloud-based, distributed computing capabilities and its ability to integrate large volumes of multi-source data, GEE has radically changed the conventional research paradigm in precipitation monitoring. At the data-source level, GEE combines long-term precipitation forecasts, including GPM IMERG, CHIRPS, and ERA5-Land. With these, coupled with environmental covariates such as SRTM topography, MODIS vegetation indices, and GSOD ground-truth validation data, it has defined a multidimensional data ecosystem that has been proven using satellite, Earth-surface, and model data, known as satellite-ground-model validation. This is quite efficient in overcoming the weaknesses of very high data acquisition barriers and tedious preprocessing experienced in conventional studies.

Methodologically, research studies are currently moving away from single-technique remote sensing inversion and towards multi-technique fusion. More specifically, the joint use of spatial downscaling techniques and machine learning procedures is becoming more mature, thanks to the GEE platform. Studies have shown that, with appropriate algorithms such as Random Forest and XGBoost, coarse-resolution satellite precipitation products can be downsampled to 100-meter or kilometre resolution, and the spatial extent of precipitation characterisation in compressed terrain and urban regions can be improved by more than an order of magnitude.

Even though the GEE platform is very convenient at monitoring precipitation, the existing research still presents some challenges: first of all, the machine learning algorithms implemented into the GEE platform are still limited about hyperparameter optimization and called to support deep learning structures, second, the dissimilarities between the applicability of the multi-source precipitation products in the context of the various climatic regions and the severe precipitation events themselves need to be cross-validated more critically. Eventually, as GEE is further integrated with more dynamic overseas AI systems (such as TensorFlow) and local satellite data with denser spatiotemporal coverage are added, cloud-based precipitation monitoring studies will provide greater value for finer hydrological predictions and real-time emergency response to disasters.

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Conflicts of Interest

The authors declare no conflict of interest.

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